THE MEASUREMENT OF UNIVERSITY STUDENT'S INTENTION TO USE THE REAL-TIME ONLINE LEARNING IN SRI LANKA

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ABSTRACT

The worldwide education system has experienced new-normal mode of teaching and learning with the prime support of the real-time online platforms especially during COVID-19 pandemic. However, the existing body of knowledge has not sufficiently dealt with it. To explore the student's intention to use the real-time online learning, Theory of Planned Behavior (TPB) has been adapted as the primary theoretical model. Followingly, the study attempted to decompose the TPB if the antecedents used three or more times in the literature. Consequently, the study recognized Perceived Usefulness, Perceived Ease of Use, Perceived Risk and Compatibility as the antecedents of Attitude, Perceived Self-Efficacy and Facilitating Conditions as the antecedents of Perceived Behavioral Control. This study used a structured online questionnaire to collect the responses from students of national universities in Sri Lanka. Consequently, 382 responses were collected. Data were analyzed using SmartPLS 4 and the proposed hypotheses were tested using PLS-SEM. All of the antecedents are also demonstrated to have a significant positive impact with the corresponding constructs of the TPB, in addition to the hypotheses put forth on attitude, perceived behavioral control, and subjective norm with the behavioral intention to use. The findings will be beneficial specifically to the policy makers to formulate key strategies to incorporate the real-time online learning in the education system, thus, the education will become more accessible and affordable.

Key Words: Real-time online learning, Theory of Planned Behavior (TPB), decomposed TPB, Sri Lanka.

INTRODUCTION

The rapid development of the internet and digital technologies has changed the way people access education. Internet-based online learning platforms have guaranteed the widespread availability of learning at anytime and anywhere, in contrast to traditional classroom-based learning (Gao, 2019). As a result, online learning is regarded as a convenient way to advance in one's academic career. As stated by Rosenberg (2001), online learning is timelier and more reliable, cheaper and provides accessibility to valuable services, chance to collaborate with worldwide community.

Online learning can be considered into two major categories namely synchronous and asynchronous learning. On the one hand, asynchronous learning is free from time and place related boundaries and is more self-paced and fewer instructor support (Bernard et al., 2004; Murphy et al., 2011; Xie et al., 2018). On the other hand synchronous learning attempts to enrich learning experience with real time communication, instant instructor support and natural language usage (Blau et al., 2017). But asynchronous learning challenges the richness and naturalness of the media. Media richness stands the extent to which the media provides instant feedback, allows verbal and non-verbal communication, customization and permits the natural language (Blau et al., 2017). Naturalness means extent to which media allows natural way of communication like face to face communication (Blau et al., 2017). Asynchronous learning is beneficial as it is more self-paced and enables participants to share knowledge or ideas without relying on the concurrent participation of other participants (Ogbonna et al., 2019). However, as per Hartnett (2015), in the asynchronous learning environment benefits to students will severely depend on the extent to which they have the facility to organize studies at home, self-study skills with the motivation and follow the learning objectives. Also, the sufficient digital skills are needed to guarantee the effectiveness of the online leaning (Kim et al.,2019).

Synchronous online learning is advantageous in many aspects namely logistical, instructional and economical (Hannum, 2001). Logistical advantages demonstrate the flexible nature of the synchronous learning where teaching and learning process can be done irrespective of the locational boundary. In synchronous learning, the interaction is facilitated with the enriched multimedia resources, is called as instructional advantages. Moreover, the learning through synchronous online learning platforms eliminates cost related to travelling and time while allowing interaction of experts across the world (Hannum, 2001). In synchronous learning, academicians can incorporate various strategies to ensure that students are not distracted by asking frequent questions through text or audio Most interestingly, the recording can be made available in the asynchronous platforms for the future reference unlike traditional learning (Chen et al., 2005). Student's motivation and commitment for learning is therefore enhanced in synchronous online learning (Hrastinski, 2008). Thus, it is termed as "Live" or "Real-time" learning (Chen et al., 2005).

Asynchronous learning is a popular online learning system because it requires less network capacity and simpler technology (Hotcomm, 2003). Specifically, during COVID-19 pandemic, worldwide education system has mainly adopted a new learning model centered on real-time online learning platforms such as Zoom, Microsoft Teams to ensure continuous teaching and learning activities. Though the situation necessitated the focus on real-time online learning, most of the studies focused on asynchronous online learning platforms namely Moodle (Ilyas and Zaman, 2020; Ngafeeson and Gautam, 2021) MOOC (Yang & Su, 2017; Wang et al., 2020; Ishak, 2020) e-learning systems in general (Leejoeiwara, 2013; Hadadgar et al., 2016; Mo et al., 2021). It evidences that literature has not adequately dealt with real-time online learning (Chen et al., 2005).

Furthermore, studies on online learning have shown that students have mixed feelings about it. Some studies demonstrated that students encountered huge stress (Patricia, 2020), lower learning and difficulties in attentiveness (Besser et al., 2020), problems related to the lack of internet connectivity (Adnan & Anwar, 2020), loss of confidence in using technology especially the older adults (Nimrod, 2018), disengagement and lesser motivation (Adnan & Anwar, 2020). Moreover, online learning is considered unpleasant as it reduces motivation, self-efficacy and cognitive engagement. In the descriptive research design (Alawamleh et al., 2020) declared that online leaning has negative impact on student teacher communication and interaction.

Contrastingly, according to Kalpana and Vinayak (2018) and Warnecke & Pearson (2011), students perceived online leaning platform to be useful and beneficial in increasing performance thus, well-designed online learning tools need to be implemented by universities and institutes in order to add more value to the learning processes. This finding aligned with the results of Teo et al. (2011) where tutor quality, perceived usefulness, and facilitating conditions were used to measure e-learning acceptance and reveled young students with technological skills adopts e-learning more. Bali & Liu (2018) demonstrated that there are no statistically significant differences in learning approaches though face to face learning observed to be higher than online learning in terms of social presence, social interaction, and satisfaction. These controversial findings indicate that student's intention to use online learning needs to be empirically investigated with sound theoretical framework to understand student's intention to use real-time online learning.

Although many studies considered Theory of Planned Behavior (TPB) to predict intention to use online learning, it has not been adequately decomposed to understand the impact of each salient beliefs on it. Also, the contradictory findings from the previous studies indicated the need for the further empirical validation. Interestingly, non-availability of Sri Lankan studies with proper theoretical frame requires researcher to deepen the focus on real-time online learning in the Sri Lankan context.

Thus, this study focuses on following research objectives;

Research Objectives

1. To identify the frequently used antecedents with TPB to explore the intention to use the real-time online learning in Sri Lanka.
2. To demonstrate the impact of decomposed TPB (DTPB) on university student's intention to use the real-time online learning in Sri Lanka.

LITERATURE REVIEW

This section focuses on delivering a broad picture of main theoretical framework of the study and studies concerning online learning adoption.

Theory of Planned Behavior (TPB)

TPB is the extended version of the Theory of Reasoned Action (TRA) (Fishbein and Ajzen, 1975; Ajzen and Fishbein, 1980). Due to the shortcoming of TRA in dealing with behavior in which people have less volitional control, TPB has evolved (Ajzen, 1988). Ajzen (1991) emphasized that behavioral intention is influenced by three constructs namely attitude, subjective norm and perceived behavioral control. Interestingly, TPB identifies behavioral belief, normative belief and control belief which influences attitude, subjective norm and perceived behavioral control respectively.

TPB has been decomposed by Taylor & Todd (1995). Attitude has been identified with three external factors namely perceived usefulness, perceived ease of use and compatibility. Subjective norm has been decomposed with the peer influence and superior influence (Taylor & Todd, 1995). Perceived Behavioral Control were identified with three factors namely perceived self-efficacy, resource facilitating condition and technology facilitation condition (Taylor & Todd, 1995). Moreover, Taylor & Todd (1995) emphasized that TPB has a greater explanatory power compared to TPB if it is decomposed as it paves a way to understand the antecedent's behavior with the main constructs. DTPB provides a complete way and relevant to recognize factors affecting individual adoption to technology whereas TPB only deals with structure of beliefs and intention to use (Suoranta & Mattila, 2004).

Studies related to Online Learning

Online learning refers to any type of learning that relies on or is enhanced by electronic communication via the most recent information and communication technologies (Boumans, 2004). Online instruction has two modes of interaction: synchronous and asynchronous. Asynchronous learning allows for multiple interactions between a teacher and a student (Chen et al., 2005). Synchronous learning requires both parties to be present simultaneously for effective teaching and learning (Chen et al., 2005). Followingly, studies related to online learning is presented in the chronological order;

Ndubisi (2004) assessed the e-learning adoption using Blackboard using DTPB in Malaysia. The study decomposed the attitude with usefulness, ease of use and security, subjective norm with course leader's influence and perceived behavioral control with self-efficacy, computer experience, training, technology facilitation, and computer anxiety. Hierarchical multiple regression analysis has been used for data analysis. The model predicted 24% of the intention whereas 42% of attitude, 10% of subjective norm and 22% perceived behavioral control has been predicted. Followingly, Cheon et al. (2012) explored readiness to mobile learning in USA with 177 students. Structural Equation Modelling (SEM) was used for data analysis. Core constructs of TPB had identified with two antecedents with each where attitude with usefulness and ease of use, subjective norm with instructor and student readiness and behavioral control with self-efficacy and learner autonomy. The model predicted 87.2% of the variation.

Tagoe & Abakah (2014) investigated students' readiness for distance learning using mobile learning in Ghana with 400 students. TPB has been used as the main theoretical foundation. Consequently, attitude, subjective norm, and perceived behavioral control influenced intention. According to Santos & Okazaki (2013), only attitude and subjective norm influenced adoption to e-learning among Brazilian faculty member. The study used DTPB among 446 faculty members and data were analyzed using SEM. They decomposed attitude with usefulness, ease of use, relative advantage and compatibility, perceived behavioral control with facilitating resources and interactivity and subjective norm with peer influence.

Leejoeiwara (2013) analyzed adoption of online learning with the self-directed learning. DTPB were used and SEM were used to analyze the data from 542 students in Thailand. Moreover, attitude was decomposed with perceived relative advantage, simplicity, compatibility, trialability, observability, subjective norm with peer, family, superior, community and external influence and self-efficacy, resource and technology facilitation were identified as antecedents of perceived behavioral control. All the identified association were significant except attitudinal antecedents namely relative advantage and trialability and external influence of subjective norm.

Ismail & Hosseini (2014) attempted to decompose the antecedents of the attitude of TPB to demonstrate the impact of students' knowledge sharing intention through e-learning systems in Malaysia. As per the findings, the attitude was significantly influenced by perceived usefulness and perceived ease of use, trust, and educational compatibility. This model explains 81% variation in attitude, and attitude explains nearly 60% of the variance of intention. Furthermore, Altawallbeh et al. (2015) studied adoption to e-learning with DTPB among academicians from the Jordanian universities. The study used 245 valid responses and analyzed using hierarchical multiple regression model. Attitude has decomposed with usefulness and ease of use, subjective norm has decomposed normative belief, perceived behavioral control has decomposed to internet self-efficacy, perceived accessibility and university support. The results revealed that only attitude and perceived behavioral control influenced behavioral intention.

Yang & Su (2017) studied student's behavior in MOOC with the integration of Technology Acceptance Model (TAM) and TPB in OpenCourseWare, Khan Academy, and Massive Open Online Courses (MOOCs). The study used PLS-SEM to analyze the data collected from 212 students. The results supported all the proposed hypotheses with the 68.7% prediction on intention. Moreover, Lai (2017) investigated use of Web 2.0 tools for learning in Taiwan using DTPB developed by Taylor & Todd (1995). It has predicted 73.1% of variation of intention.

Khasawneh (2017) studied attitude with the attitudinal beliefs such as usefulness, ease of use, trialability, observability and computer self-efficacy in Jordan. The model predicted 35.57% of behavioral intention. Furthermore, study conducted to investigate the adoption to WhatsApp learning of Mzuzu University in Malawi used quantitative questionnaire and semi-structured interviews. The collected data were analyzed descriptively using SPSS. The results revealed that WhatsApp is beneficial in learning as it provides instant data sharing, academic communication even after the class hours (Nyasulu & Chawinga, 2019). Also, study conducted by Gomez-Ramirez et al. (2019), investigated mobile learning with DTPB in Colombia. SPSS has been used for the data analysis. Further, usefulness and ease of use with attitude, instructor readiness, student's readiness with subjective norm and self-efficacy and learner autonomy with facilitating condition has identified as antecedents.

Nadlifatin et al. (2020) measured intention to use blended learning system with the integrated model of TAM and TPB in Taiwan and Indonesia. Only attitude was identified with two antecedents namely usefulness and ease of use. Notably, 41% of behavioral intention in Taiwan and 28% of Behavioral intention of Indonesia has been explained in the model. Also, Wang et al. (2020) analyzed leaner's behavior in MOOC in China. Online questionnaire from 638 students were collected and SEM were used for data analysis. Only attitude has decomposed with two factors namely usefulness and ease of use. The results revealed attitude, usefulness, subjective norm and behavioral control were significant and ease of use was not identified as a significant antecedent of attitude.

He et al. (2020) studied the importance of digital competence in student's digital informal learning in Belgium. Attitude has been decomposed to many antecedents, namely perceived ease of use, perceived usefulness, perceived enjoyment, educational compatibility and perceived behavioral control were further decomposed into facilitating conditions and digital competence. The study used SEM for data analysis and predicted 49% of the intention.

Kim et al. (2021) studied Korean student's acceptance towards online learning system. The study integrated TPB with TAM and analyzed the moderation effect of user innovativeness. Study used SEM for data analysis and results emphasized that only usefulness influenced attitude and also behavioral intention was influenced by attitude and subjective norm. Further, user innovativeness moderated the relationship between subjective norm and intention. In addition, Yao et al. (2022) conducted the study in Henan province China with 429 college students. The study integrated TAM with TPB with additional variable of Self-awareness relating to TAM and TPB constructs. Hypotheses were tested using SEM. The model explained 83.6% of the intention. Table 1 summaries the articles related to DTPB.

Perceived Risk and Online Learning

students naturally expose to numerous privacy-related risks when learning happens through real-time online platforms. It will have the chance of influencing the learner's motivation (Page & White, 2002). The perceived risk will negatively influence the adoption intention of current participants and future students who are yet to be enrolled in national universities (Liebermann & Stashevsky, 2002; Kim, 2021). Thus, the security risk is not only attributed to e-commerce participants but also, to students who engage in learning activities via real-time online learning platforms exposed to various security-related concerns (Kim, 2021).

Featherman & Pavlou (2003) have proposed different ways in which risk can be perceived in the context of e-service adoption. They identified six facets of risk, namely performance risk, financial risk, time risk, psychological risk, social risk, and privacy risk. Privacy and security risk are most prevalent in the current era (Kim, 2021). Thus, perceived risk needs to be recognized as a vital factor in online learning related studies. But perceived risk has been rarely considered. The study on South Korea in 2020 considered security concerns and privacy concerns as the external variable of Perceived Ease of Use. It indicates that the abovementioned concerns negatively influence Perceived Ease of use (Kim, 2021). Further, Perceived Usefulness and peer behavior significantly influence intention to use real-time online classes. However, Perceived Ease of Use does not. Moreover, this model contributes to nearly 68.8% variation in intention. Also, security concerns were further considered with the TRA's subjective norm to investigate intention to adopt Zoom application in Vietnam (Long & Khoi, 2020). The study revealed a significant negative influence on the subjective norm.

However, perceived risk has been considered as the antecedents of primary constructs of the TPB in other related fields, namely attitude (Lee, 2009; Liao et al., 2010; Sanayei & Bahmani, 2012; Xie et al., 2017) and perceived behavioral control (Xie et al., 2017). According to the researchers' knowledge, the studies that dealt with online learning are void with TPB. Nevertheless, there are pieces of evidence with TAM and TRA (Long & Khoi, 2020; Kim, 2021).

Table 1. Summary of the articles on the DTPB application

Attitude	Perceived usefulness	(Ndubisi, 2004) (Cheon et al., 2012) (Santos & Okazaki, 2013) (Tagoe & Abakah, 2014) (Ismail & Hosseini, 2014) (Altawallbeh et al., 2015) (Yang & Su, 2017) (Lai, 2017) (Khasawneh, 2017) (Gomez-Ramirez et al., 2019) (Nadlifatin et al., 2020) (He et al., 2020) (Wang et al., 2020) (Kim et al., 2021) (Yao et al., 2022)	15	17.65%
	Perceived ease of use	(Ndubisi, 2004) (Cheon et al., 2012) (Santos & Okazaki, 2013) (Tagoe & Abakah, 2014) (Ismail & Hosseini, 2014) (Altawallbeh et al., 2015) (Lai, 2017) (Khasawneh, 2017) (Yang & Su, 2017) ((Gomez-Ramirez et al., 2019) (He et al., 2020) (Nadlifatin et al., 2020) (Wang et al., 2020) (Kim et al., 2021) (Yao et al., 2022)	15	17.65%
	Perceived Compatibility	(Santos & Okazaki, 2013) (Leejoeiwara, 2013) (Ismail & Hosseini, 2014) (Lai, 2017) (He et al., 2020)	05	5.88%
	Trialability	(Leejoeiwara, 2013) (Khasawneh, 2017)	02	2.35%
	Observability	(Leejoeiwara, 2013) (Khasawneh, 2017)	02	2.35%
	Computer Self-efficacy	(Khasawneh, 2017)	01	1.18%
	Perceived enjoyment	(He et al., 2020)	01	1.18%
	Trust	(Ismail & Hosseini, 2014)	01	1.18%
	Self-awareness	(Yao et al., 2022)	01	1.18%
	Security	(Ndubisi, 2004)	01	1.18%
	Perceived Simplicity	(Leejoeiwara, 2013)	01	1.18%

Subjective Norm	Relative advantage	(Santos & Okazaki, 2013) (Leejoeiwara, 2013)	02	2.35%
	Peer influence	(Santos & Okazaki, 2013) (Leejoeiwara, 2013) (Lai, 2017)	03	3.53%
	Superior Influence	(Leejoeiwara, 2013) (Lai, 2017)	02	2.35%
	Course leader's influence	(Ndubisi, 2004)	01	1.18%
	Family influence & External Influence & Community Influence	(Leejoeiwara, 2013)	01	1.18%
Perceived Behavioural Control	Student readiness	(Cheon et al., 2012) (Tagoe & Abakah, 2014) (Gomez-Ramirez et al., 2019)	03	3.53%
	Instructor Readiness	(Cheon et al., 2012) (Gomez-Ramirez et al., 2019)	02	2.35%
	Self-awareness	(Yao et al., 2022)	01	1.18%
	Self-Efficacy	(Ndubisi, 2004) (Cheon et al., 2012) (Leejoeiwara, 2013) (Tagoe & Abakah, 2014) (Altawallbeh et al., 2015) (Lai, 2017) (Gomez-Ramirez et al., 2019)	07	8.24%
	Facilitating Condition	(Ndubisi, 2004) (Santos & Okazaki, 2013), (Leejoeiwara, 2013) (Lai, 2017) (He et al., 2020)	05	5.88%
	Computer experience & Training & Computer anxiety	(Ndubisi, 2004)	01	1.18%
	Perceived accessibility & University support	(Altawallbeh et al., 2015)	01	1.18%
	Learning autonomy	(Cheon et al., 2012) (Tagoe & Abakah, 2014) (Gomez-Ramirez et al., 2019)	03	3.53%
	Self-awareness	(Yao et al., 2022)	01	1.18%
	Interactivity	(Santos & Okazaki, 2013)	01	1.18%
	Digital Competence	(He et al., 2020)	01	1.18%

In summary, due to the scarce of studies deals with decomposed TPB in real-time online learning setting, this research intends understand adoption to real-time online learning by decomposing TPB. Researcher extensively reviewed online learning related articles for the period of 2002 to 2022. Literature review identified several gaps in the online learning context.

Firstly, most of the researchers studied online learning using TPB. But, there is a lack in the decomposition of the theory to comprehend the effect of each belief on the primary constructs of TPB (Leejoeiwara, 2013; Lai, 2017; Gomez-Ramirez et al., 2019; Cheon et al., 2012; Tagoe & Abakah, 2014; He et al., 2020). None of the studies has been conducted in the Sri Lankan context.

Secondly, existing studies related with TPB and DTPB has accounted for controversial findings. In summation, concerning TPB, many studies revealed that attitude, subjective norms, and perceived behavioral control exerted significant influence on adoption intention (Al-Harbi, 2011; Gomez-Ramirez et al., 2019; Yang & Su, 2017; Ilyas & Zaman, 2020, Cheon et al., 2012; Leejoeiwara, 2013;Lai, 2017; Wang et al., 2020). Some researchers demonstrated that neither perceived behavioral control (Teo & Lee, 2010; Kim et al., 2021; Santos & Okazaki, 2013) nor subjective norm (Hadadgar et al., 2016; He et al., 2020; Tagoe & Abakah, 2014) plays a significant role in determining intention to use. In many studies, the attitude was the most influencing construct on intention decision. However, in contrast, studies have shown perceived behavioral control as the first significant determinant of adoption intention (Clutterbuck et al., 2015; Cheon et al., 2012; Tagoe & Abakah, 2014). Also, the attitude has not significantly influenced behavioral intention in some studies (Masruf & Teng, 2016). These controversies indicate that the existing knowledge cannot be applied directly to predict the acceptance of technology in different context. Thus, there is a need for the new study to understand Sri Lankan students' intention to adopt online learning.

Thirdly, many studies explored online learning with asynchronous learning platforms such as Moodle (Ilyas & Zaman, 2020; Ngafeeson & Gautam, 2021) MOOC (Wang et al., 2020; Ishak, 2020; Yang & Su, 2017) e-learning systems in general (Mo et al., 2021; Hadadgar et al., 2016; Leejoeiwara, 2013). However, very few have dealt with the real-time online learning platform. Among them, some evidence with TAM (Alfadda & Mahdi, 2021; Purwanto & Tannady, 2020; Bhatt & Shiva, 2020; Faisal et al., 2021; Kim, 2021) and TRA

(Long & Khoi, 2020). It is also noteworthy that none of those above studies were attempted to assess the adoption of real-time online learning using TPB in international and Sri Lankan context.

In addition, TPB has proved its successful application by combining perceived risk in various phenomena such as Internet banking (Sanayei & Bahmani, 2012; Obaid & Aldammagh, 2021; Kim et al., 2016) online shopping (Kim, 2020; Ha, 2020) e-government (Xie et al., 2017) and e-health (Gu et al., 2019). Even though many online related researches discussed students' perception of online learning using many theoretical perspectives, very few of them had recognized perceived risk as a vital factor.

Finally, few descriptive studies have been investigated students' perception of online learning in Sri Lankan context (Vidanagama, 2016; Jayakananthan & Jeyaraj, 2019; Samsudeen & Mohamed, 2019; Pirapuraj et al., 2019; Selvaras, 2020; Rameez et al., 2020; Nafrees et al., 2020; ; Nawaz & Mohamed, 2020; Abdullah et al., 2021; Nayanajith & Damunupola, 2021). It has also been noticed that the studies available in the local context lack the application of PLS-SEM approaches though it is being extensively applied to study the adoption of online learning. Conclusively, this study is conducted to address above-specified lapses in the existing knowledge.

Definition of Variable

This section defines the concepts of the study.

- *Attitude:* Attitude refers to an individual's evaluative judgments about the consequences of using real-time online learning (Ajzen, 1991).
- *Perceived Usefulness:* Perceived Usefulness stands to the extent to which students perceive that real-time online learning is beneficial to enhancing performance (Davis, 1989).
- *Perceived Ease of Use:* Perceived Ease of Use refers to the degree to which students feel that real-time online learning is easier to use and free from additional effort (Davis, 1989).
- *Compatibility:* Compatibility represents the extent to which students perceive that real-time online learning is well-suited according to their needs and experiences (Rogers, 2003).
- *Perceived Security Risk:* It refers to the students' negative perception about the uncertainty involved concerning the deprival of personally identifiable information in real-time online learning (Featherman & Pavlou, 2003).
- *Subjective Norm:* Subjective norm explains students' belief about the degree to which referent others will influence their learning through real-time online learning (Ajzen, 1991).
- *Perceived Behavioral Control:* It refers to students' perception of the ease or difficulty of adopting real-time online learning (Ajzen, 1991).
- *Perceived Self-Efficacy:* It refers to the extent to which the learners have confident about his/her capability to use real-time online learning (Bandura,2005).
- *Facilitating Conditions:* Facilitating Conditions means persons' perception of the degree to which organizational and technological resources are available to facilitate real-time online learning usage (Venkatesh et al., 2003).

METHOD

This study attempted to postulate hypotheses and validate them through empirical investigation. Thus, the research follows deductive approach with positivist perspective. Additionally, a self-administered questionnaire survey has been employed as the research strategy. Also, the research choice of this study is the mono-method as it uses single quantitative data collection technique and data analysis using statistical techniques.

Conceptualization & Hypotheses Development

Attitude

Among the previous researches, it has been empirically proved that attitude exerts positive influence on behavioral intention to use (Cheon et al., 2012; Leejoeiwara, 2013; Tagoe & Abakah, 2014; Ismail & Hosseini, 2014; Clutterbuck et al., 2015; Hadadgar et al., 2016; Lai, 2017; Mangir et al., 2017; Yang & Su, 2017; Khasawneh, 2017; Buabeng-Andoh, 2018; Gomez-Ramirez et al., 2019; Nadlifatin et al., 2020; Ilyas & Zaman, 2020; Gao, 2020; He et al., 2020; Purwanto & Tannady, 2020; Bhatt & Shiva, 2020; Long & Khoi, 2020; Alfadda & Mahdi, 2021).

Hence, based on the above premise, the following hypothesis is proposed;

> H1: Attitude will positively influence the Behavioral Intention to Use real-time online learning.

Perceived Usefulness

Many past studies have justified that the positive impact of perceived usefulness exists with attitude (Cheon et al., 2012; Tagoe & Abakah, 2014; Ismail & Hosseini, 2014; Lai, 2017; Yang & Su, 2017; Khasawneh, 2017; Buabeng-Andoh, 2018; Gomez-Ramirez et al., 2019; Nadlifatin et al., 2020; Wang et al., 2020; Gao, 2020; He et al., 2020; Purwanto & Tannady, 2020; Bhatt & Shiva, 2020; Alfadda & Mahdi, 2021; Kim et al., 2021)

Hence, based on the above premise, the following hypothesis is proposed;

> H2: Perceived Usefulness positively affects Attitude to adopt real-time online learning.

Perceived Ease of Use

Many researchers reported a positive effect of Perceived Ease of Use on attitude (Cheon et al., 2012; Tagoe & Abakah, 2014; Ismail & Hosseini, 2014; Lai, 2017; Yang & Su, 2017; Khasawneh, 2017; Buabeng-Andoh, 2018; Gomez-Ramirez et al., 2019). With TAM also reported to have the positive impact (Purwanto & Tannady, 2020; Bhatt & Shiva, 2020 Alfadda & Mahdi, 2021).

Hence, based on the above premise, the following hypothesis is proposed;

> H3: Perceived Ease of Use positively affects Attitude to adopt real-time online learning.

Compatibility

Many researchers empirically proved that compatibility has a positive effect on attitude (Santos & Okazaki, 2013; Ismail & Hosseini, 2014; Lai, 2017; He et al., 2020).

Hence, based on the above premise, the following hypothesis is proposed;

> H4: Compatibility will positively affect Attitude to adopt real-time online learning.

Perceived Security Risk

Previous studies have proven the negative impact of perceived risk on attitude (Lee, 2009; Sanayei & Bahmani, 2012; Liao et al., 2010; Xie et al., 2017).

Hence, based on the above premise, the following hypothesis is proposed;

> H5: Perceived Risk will negatively affect Attitude to adopt real-time online learning.

Subjective Norm

Positive effect subjective norm on behavioral intention to use has been empirically proved by numerous scholars (Cheon et al., 2012; Leejoeiwara, 2013; Tagoe & Abakah, 2014; Clutterbuck et al., 2015; Masruf & Teng, 2016; Lai, 2017; Mangir et al., 2017; Yang & Su, 2017; Buabeng-Andoh, 2018; Gomez-Ramirez et al., 2019; Nadlifatin et al., 2020; Ilyas & Zaman, 2020; Wang et al., 2020; Kim et al., 2021).

Hence, based on the above premise, the following hypothesis is proposed;

H6: Subjective Norm will positively influence the Behavioral Intention to Use real-time online learning.

Perceived Behavioral Control

Positive impact of perceived behavioral control on intention to use the online education platforms has been proved by many researchers (Cheon et al., 2012; Leejoeiwara, 2013; Tagoe and Abakah, 2014; Clutterbuck et al., 2015; Masruf & Teng, 2016; Hadadgar et al., 2016; Lai, 2017; Mangir et al., 2017; Yang & Su, 2017; Gomez-Ramirez et al., 2019; Nadlifatin et al., , 2020; Ilyas & Zaman, 2020; Wang et al., 2020; Gao, 2020; He et al., 2020; Ngafeeson & Gautam, 2021).

Hence, based on the above premise, the following hypothesis is proposed;

H7: Perceived Behavioral Control will positively influence the Behavioral Intention to Use real-time online learning.

Perceived Self-Efficacy

Previous research shows a positive impact on perceived behavioral control (Cheon et al., 2012; Leejoeiwara, 2013; Tagoe & Abakah, 2014; Lai, 2017; Gomez-Ramirez, 2019).

Hence, based on the above premise, the following hypothesis is proposed;

H8: Perceived Self-Efficacy positively affects Perceived Behavioral Control to adopt real-time online learning.

Facilitating Conditions

Positive impact of facilitating conditions and perceived behavioral control has been proved by some researchers (Leejoeiwara, 2013; Lai, 2017;).

Hence, based on the above premise, the following hypothesis is proposed;

H9: Facilitating conditions will positively affect Perceived Behavioral Control to adopt real-time online learning.

Figure 1 portrays the conceptual model of the study.

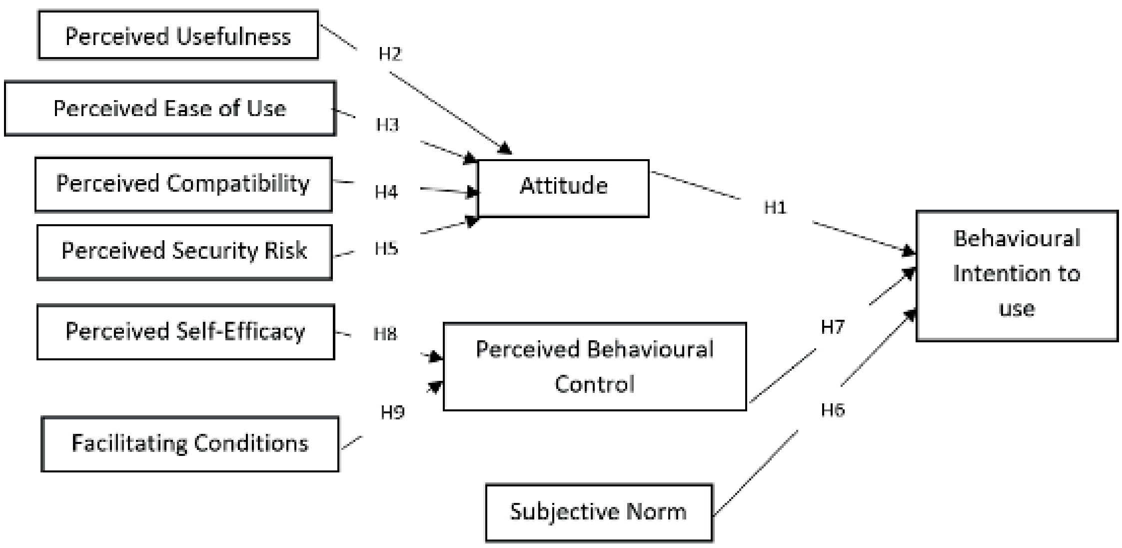

Figure 1. Conceptual framework of the study

Participants

The study's target population is undergraduates enrolled in the state universities of Sri Lanka. Altogether fifteen universities are located across nine provinces in Sri Lanka (UGC Sri Lanka, 2020). The Table 2 depicts the universities and their associated provinces of them. Based on the convenience sampling technique, study data were collected since this is an easy technique to access the widespread sample (Sekaran, 2003). The responses were collected in 2023. From 400 sample units, during the inspection process, 18 were removed due to the incompleteness and 382 valid responses were considered in the study.

Table 2. Universities with associated provinces

University	Province
Rajarata University	North Central
Wayamba University	North Western
Sabaragamuwa University	Sabaragamuwa
University of Peradeniya	Central
Uva Wellassa University	Uva
University of Ruhuna	Southern
University of Sri Jayewardenepura	Western
University of Colombo	
University of Kelaniya	
University of Moratuwa	
Open University	
University of the Visual and Performing Arts	
University of Jaffna	Northern
Eastern University	Eastern
South Eastern University	

Data Collection and Analysis

According to Sekaran (2003), the questionnaire is a very efficient data collection method in which well-organized questions will be asked from respondents where they need to provide the answer. In this study, the questionnaire was distributed electronically using e-mails, WhatsApp groups, and Facebook messenger. Questionnaire has been adapted from literature and modified according to the needs of the study. Table 3 and Table 4 respectively represents the literature sources of the items adapted and items used for this study. The Five-point Likert scale were used to assign weights to measure the model variables and "5" for strongly agree, "4" for agree, "3" for neither agree nor disagree, "2" for disagree, and "1" for strongly disagree (Allen & Seaman, 2007). Because, Likert scale is recommended for rating questions (Saunders et al., 2007).

The partial least square structural equation modeling has been used to test the hypothesis using SmartPLS 4 (Ringle et al., 2005). Assessment of measurement model indicates the relationship between items and the latent variable being studied. It can be evaluated using reliability and validity tests, namely convergent and discriminant validity. The structural model assessment needs to be tested for multicollinearity using VIF and Tolerance. Furthermore, the coefficient of determination will be used to measure the dependent variable's variance caused by all concerned predictors. PLS-SEM path co-efficient is used to test the hypothesis with associated t-values and p-values.

Table 3. Variables with literature sources

Variables	Items	Literature sources
Attitude	04	(Taylor & Todd, 1995)
Perceived Usefulness	07	(DeLone & Mclean, 2003; Chiu & Wang, 2008; Ho & Dzeng, 2010; Hassanzadeh et al., 2012)
Perceived Ease of Use	05	(DeLone & Mclean, 2003; Wang & Liao, 2008)
Perceived Compatibility	03	(Taylor & Todd, 1995)
Perceived Security Risk	04	(Featherman & Pavlou, 2003; Gefen, 2000; Kim, 2020)
Perceived Behavioural Control	03	(Wu & Chen, 2005)
Perceived Self-Efficacy	03	(Taylor & Todd, 1995)
Facilitating Conditions	03	(Venkatesh et al., 2012)
Subjective Norm	03	(Wu & Chen, 2005)
Behavioural intention to use	03	(Cheng et al., 2006)

Table 4. Variables with items

Attitude (ATT)	ATT_01	Using real-time online learning is a good idea
	ATT_02	Using real-time online learning is a wise idea
	ATT_03	I like the idea of using real-time online learning
	ATT_04	Using real-time online learning would be pleasant
Perceived Usefulness(PU)	PU_01	I think that real-time online learning helps to save time
	PU_02	I think that real-time online learning helps to save cost
	PU_03	I think that real-time online learning helps me to be self-reliable
	PU_04	I think that real-time online learning helps to improve my knowledge
	PU_05	I think that real-time online learning helps to improve my performance
	PU_06	I think that real-time online learning is effective
	PU_07	I think that real-time online learning is efficient
Perceived Ease of Use(PEOU)	PEOU_01	I think that real-time online learning is easy to use
	PEOU_02	I think that real-time online learning is easy to learn
	PEOU_03	I think that real-time online learning is easy to access
	PEOU_04	I think that real-time online learning is easy to understand
	PEOU_05	I think that real-time online learning is convenient
Perceived Compatibility(COM)	COM_01	Using real-time online learning will fit well with the way I learn.
	COM_02	Using real-time online learning will fit into my learning style.
	COM_03	The setup of real-time online learning will be compatible with the way I learn.
Perceived Security Risk(PSR)	PSR_01	I do not feel secure about online learning resources or tools used in real-time online learning.

	PSR_02	I am concerned that online learning resources or tools providers will not implement appropriate security measures for user protection.
	PSR_03	I am concerned that hacking happened in real-time online learning will lead to disclosing my personal information.
	PSR_04	I am concerned that hackers will disrupt my online class due to the poor security of online learning resources or tools.
Perceived Behavioral Control(PBC)	PBC_01	Using real-time online learning is entirely within my control
	PBC_02	I have the resources, knowledge, and ability to make use of real-time online learning
	PBC_03	I think that I would be able to use real-time online learning well for my learning activities
Perceived Self-Efficacy(PSE)	PSE_01	I would feel comfortable using real-time online learning system on my own.
	PSE_02	If I want to, I can use real-time online learning system on my own easily.
	PSE_03	I would be able to use real-time online learning system even if there is no one around to show me how to use it.
Facilitating Conditions(FC)	FC_01	I have the resources necessary to use real-time online learning.
	FC_02	I have the knowledge necessary to use real-time online learning.
	FC_03	Real-time online learning is compatible with other technologies I use.
Subjective Norm (SN)	SN_01	People who influence my behavior would think that I should use real-time online learning
	SN_02	People who are important to me would think that I should use real-time online learning
	SN_03	People whose opinions are valued to me would think that I should use real-time online learning
Behavioral Intention to Use(BITU)	BITU_01	I would use real-time online learning for my learning needs.
	BITU_02	Using real-time online learning for learning is something I would do.
	BITU_03	I would see myself using real-time online learning for doing my learning activities.

FINDINGS

Assessment of the Measurement Model

Measurement model can be evaluated using reliability and validity tests namely convergent and discriminant validity (Chin, 1998). Convergent validity measures the related items of a construct are loaded significantly with each other whereas discriminant validity assesses two unrelated constructs are not significantly loaded with each other (Sekaran, 2003).

Reliability of the Constructs and Indicators

Reliability test is used to measure the internal consistency of constructs and indicators. In this study, cronbach's alpha and composite reliability have been used to measure the construct reliability (Dakduk et al., 2019) and to assess the indicator reliability outer loading has been used (Hulland, 1999; Wong, 2013).

Generally, Cronbach's Alpha value lies less than 0.60 is considered low, 0.70 is considered acceptable, and greater than 0.80 is considered excellent internal consistency (Sekaran, 2003). Due to the conservative measurement of the Cronbach's Alpha, Dakduk et al. (2019) suggested composite reliability is referred to as McDonald's coefficient, to measure the construct reliability. It is needed to be loaded to 0.70 or above in order to ensure the composite reliability (Bagozzi and Yi, 1988; Dakduk et al., 2019). Also, the outer loadings of the indicator are needed to be loaded with 0.70 or above is preferred, but 0.4 or greater is adequate (Hulland, 1999; Wong, 2013). As per the Table 5, Cronbach's alpha, composite reliability is above the acceptable value of 0.70 and factor loadings are above 0.50. Thus, it can be concluded that the internal consistency of constructs and indicators is well-established.

Table 5. Reliability of the constructs and indicators

Construct	Items	Item loadings	Cronbachalpha	Composite reliability
ATT	ATT1	0.735	0.825	0.843
	ATT2	0.574		
	ATT3	0.833		
	ATT4	0.805		
PU	PU1	0.683	0.896	0.904
	PU2	0.584		
	PU3	0.799		
	PU4	0.759		
	PU5	0.711		
	PU6	0.873		
	PU7	0.783		
PEOU	PEOU1	0.664	0.893	0.900
	PEOU2	0.820		
	PEOU3	0.762		
	PEOU4	0.805		
	PEOU5	0.895		
COM	COM1	0.918	0.923	0.923
	COM2	0.871		
	COM3	0.893		
PSR	PSR1	0.541	0.873	0.896
	PSR2	0.837		
	PSR3	0.798		
	PSR4	0.947		
PBC	PBC1	0.749	0.849	0.854
	PBC2	0.805		
	PBC3	0.868		
FC	FC1	0.832	0.880	0.885
	FC2	0.817		
	FC3	0.858		
	FC4	0.709		
PSE	PS1	0.853	0.874	0.875
	PS2	0.839		
	PS3	0.816		
SN	SN1	0.861	0.896	0.896
	SN2	0.869		
	SN3	0.854		
BITU	BITU1	0.892	0.916	0.920
	BITU2	0.819		
	BITU3	0.943		

Validity of the Constructs and Indicators

Convergent Validity

Convergent validity refers to the extent to which the items to measures the same constructs is related to one and another. To measure it, Average Variance Extracted (AVE) is used. The AVE must be assumed more than 0.50 to establish convergent validity (AVE >0.50) (Hair et al., 2010). Table 6 shows the AVE of the constructs are above 0.50. Thus, the convergent validity is established.

Table 6. Convergent validity

Construct	AVE
ATT	0.553
PU	0.557
PEOU	0.629
COM	0.799
PSR	0.632
PBC	0.654
FC	0.649
PSE	0.699
SN	0.742
BITU	0.785

Discriminant Validity

Discriminant value tests the degree to which the variables in the model are not related with the other variables in the model (Chin, 1998). In this study cross loadings, Fornell-Larcker Scale, Heterotrait-Monotrait (HTMT) ratios has been used. To assume discriminate validity, squared root of a variable's AVE need to be greater than the that of the other constructs and must be more than 0.50 (Fornell & Larcker, 1981). Cross loadings of the items in a construct are needed to be significantly loaded in the same constructs than other constructs (Cheng & Chen, 2015). Further, HTMT ratio has been used to measure the discriminate validity since it is based on the multitrait-multimethod matrix (Henseler et al., 2015). If the HTMT ratio is lower than the 0.85, the discriminate validity will be assumed (Kline, 2011). As per the cross loadings, each item in the construct are loaded in the same construct than the other. Further, Table 7 evidences the existence of the discriminant validity using Fornell-Larcker Scale. Further, Table 8 evidences the existence of the discriminant validity using HTMT Ratio. According to the statistical evidences, the discriminant validity is established.

Table 7. Assessment of discriminant validity using Fornell-Larcker Scale

	ATT	FC	BITU	PBC	COM	PEOU	PSR	PSE	PU	SN
ATT	0.744									
FC	0.619	0.806								
BITU	0.583	0.634	0.886							
PBC	0.66	0.813	0.620	0.809						
COM	0.704	0.609	0.654	0.729	0.894					
PEOU	0.741	0.722	0.654	0.756	0.727	0.793				
PSR	0.264	0.347	0.287	0.424	0.333	0.299	0.795			
PSE	0.638	0.817	0.644	0.833	0.63	0.683	0.343	0.836		
PU	0.797	0.66	0.628	0.733	0.784	0.832	0.357	0.664	0.747	
SN	0.577	0.597	0.611	0.562	0.647	0.581	0.414	0.55	0.619	0.861

Table 8. Assessment of discriminant validity using HTMT Ratio

	ATT	FC	BITU	PBC	COM	PEOU	PSR	PSE	PU	SN
ATT										
FC	0.621									
BITU	0.585	0.632								
PBC	0.663	0.814	0.618							
COM	0.703	0.608	0.651	0.729						
PEOU	0.744	0.727	0.653	0.755	0.723					
PSR	0.263	0.345	0.291	0.429	0.327	0.302				
PSE	0.638	0.818	0.644	0.834	0.629	0.684	0.337			
PU	0.799	0.663	0.628	0.738	0.784	0.834	0.362	0.666		
SN	0.58	0.597	0.611	0.566	0.646	0.582	0.414	0.55	0.617	

Assessment of the Structural Model

Multicollinearity (VIF)

Multicollinearity assesses the extent to which two or more independent variables are corelated with each other (Hair et al., 2010). Multicollinearity is detected if the variance inflation factor (VIF) is more than 5. As portrayed in the Table 9 VIF values are below 5, indicates the absence of multicollinearity (Hair et al., 2011; Ringle et al., 2015).

Table 9. Assessment of Multicollinearity using VIF

Dependent variable	Independent variable	VIF
ATT	PU	4.255
	PEOU	3.411
	COM	2.752
PBC	PSR	1.156
	PS	3.005
	FC	3.005
BITU	ATT	1.993
	PBC	1.942
	SN	1.643

Coefficient of Determination (R^2)

Coefficient of determination demonstrates the variation on the dependent variable caused by all of its independent variables (Dreheeb et al., 2016). If the R^2 value is less than 0.67, in between 0.19 to 0.33, in between 0.33 to 0.67 and more than 0.67 it will be respectively assumed extremely weak, weak, moderate and significant variance in the dependent variable Chin (1998). Table 10 summaries the R^2 value and result of the proposed model.

Table 10. R^2 of the independent variables

Construct	R^2	Adjusted R^2	Results
ATT	0.666	0.663	Moderate
PBC	0.747	0.746	Significant
BITU	0.503	0.499	Moderate

Effect Size (f^2)

The effect size measures the impact of the eliminated constructs on the independent variable (Sarstedt et al., 2017). f^2 values 0.02,0.15 and 0.35 represent small, medium and large effects respectively. As per the Table 11, perceived usefulness, perceived ease of use, compatibility and perceived security risk have respectively identified with 0.177 (medium effect), 0.04 (small effect), 0.031(small effect), 0.003(small effect) effects on attitude. Perceived self-efficacy and facilitating condition has the medium effect on the perceived behavioral control. Small effects are identified on behavioral intention to use by all of its exogenous variables namely attitude, perceived behavioral control and subjective norm.

Table 11. Assessment of Effect Size(f2)

Dependent variable	Independent variable	f^2	Results
ATT	PU	0.177	Medium
	PEOU	0.04	Small
	COM	0.031	Small
	PSR	0.003	Small
PBC	PS	0.338	Medium
	FC	0.210	Medium
BITU	ATT	0.036	Small
	PBC	0.101	Small
	SN	0.131	Small

Predictive Relevance (Q2)

Wong (2013) mentioned that the Q2 value of 0.02, 0.15, and 0.35 respectively demonstrates that predictor has a small, medium, and large predictive relevance on the dependent variable. As demonstrated in the Table 12, attitude, perceived behavioral control and behavioral intention to use has the large predictive relevance.

Table 12. Assessment of predictive relevance (Q2)

Dependent variable	Q^2	Results
ATT	0.517	Large
PBC	0.582	Large
BITU	0.454	Large

Hypotheses Testing

Table 13 and Figure 2 portray the brief of the results of the model. In summary, all the proposed hypotheses are supported. Perceived usefulness use (β= 0.501, p-value <0.05), perceived ease of use (β= 0.212, p-value <0.05), compatibility (β= 0.167, p-value <0.05), and perceived security risk (β= -0.034, p-value <0.05), has the significant impact on the behavioral intention to use, lead to the acceptance of the H2, H3, H4, H5. Hypotheses H8 and H9 are supported since the perceived self-efficacy (β= 0.507, p-value <0.05), and facilitating condition (β= 0.400, p-value <0.05), has the significant impact on the behavioral intention to use.

Table 13. Results of the hypothesis testing

Hypothesis	Relationship	path	p-value	Decision
H1	Attitude → Behavioural Intention to use	0.188	0.047	Supported
H2	Perceived Usefulness → Attitude	0.501	0.000	Supported
H3	Perceived Ease of Use → Attitude	0.212	0.000	Supported
H4	Compatibility → Attitude	0.167	0.000	Supported
H5	Perceived Security Risk → Attitude	-0.034	0.000	Supported
H6	Subjective Norm → Behavioural Intention to use	0.327	0.000	Supported
H7	Perceived Behavioural Control → Behavioural Intention to use	0.312	0.001	Supported
H8	Perceived Self-Efficacy → Perceived Behavioural Control	0.507	0.000	Supported
H9	Facilitating Conditions → Perceived Behavioural Contro	0.400	0.002	Supported

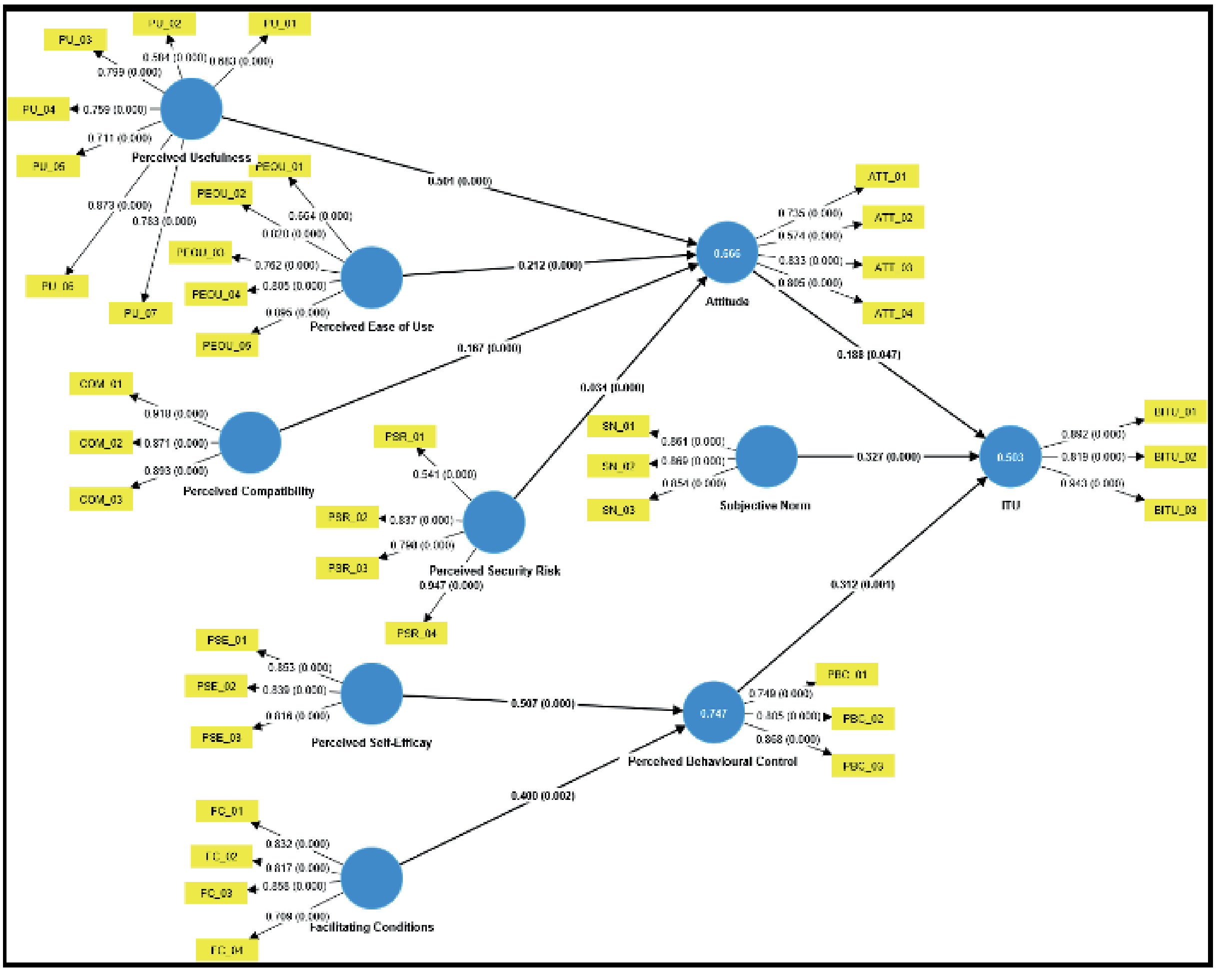

Figure 2. PLS-SEM path diagram

DISCUSSION

Research Question 01

Twenty years of published articles from 2002 to 2022 in the context of online learning has been reviewed to identify frequently considered antecedents of TPB and contradictions of the findings. The researcher attempted to find and include if an antecedent was considered more than three times in a relevant study. As per the literature, Perceived Usefulness, Perceived Ease of Use, Perceived Risk, Compatibility as the antecedents of Attitude, followingly, Perceived Self-Efficacy, Facilitating Conditions as the antecedents of Perceived Behavioral Control has been recognized as antecedents. In a nutshell, TPB has been extended by applying widely recognized antecedents to assess the adoption of real-time online learning in the Sri Lankan context.

Research Question 02

As portrayed in the Table 9, 66.6% of the variation of the attitude has been explained by the perceived usefulness, perceived ease of use, compatibility and perceived risk. Therefore, the identified variables have moderately predicted attitude. Furthermore, perceived usefulness has identified as the significant predictor of the attitude (β= 0.501, p-value<0.05), supports H2. It has supported by numerous researches too (Cheon et al., 2012; Tagoe and Abakah, 2014; Ismail and Hosseini, 2014; Lai, 2017; Yang and Su, 2017; Khasawneh, 2017; Buabeng-Andoh, 2018; Gomez-Ramirez et al., 2019; Nadlifatin et al., 2020; Wang et al., 2020; Gao, 2020; He et al., 2020; Alfadda and Mahdi, 2021; Purwanto and Tannady, 2020; Bhatt and Shiva, 2020; Kim et al., 2021). Thus, it is critical to ensure that real-time online learning benefits students since this will increase students' positive feelings/attitudes toward real-time online learning. Importantly, it needs to facilitate the enhancement of the knowledge and performance of the students while minimizing the cost and time needed to be spent in real-time online learning. Perceived ease of use has positively associated with the attitude (β= 0.212, p-value<0.05), supports H3, evidenced by (Cheon et al., 2012; Tagoe and Abakah, 2014; Ismail and Hosseini, 2014; Lai, 2017; Yang and Su, 2017; Khasawneh, 2017; Buabeng-Andoh, 2018; Gomez-Ramirez et al., 2019). Hence, it is essential to ensure that additional effort is not needed in engaging in real-time online learning. Prominently, the platform under consideration must be simple to use and user-friendly. In the future, developers of applications may consider adding new features such as audio and video aids, simulations to provide a rich learning experience.

Compatibility had the positive effect on the attitude (β= 0.167, p-value<0.05), supports H4. Similar findings were reported in the past studies (Santos and Okazaki, 2013; Ismail and Hosseini, 2014; Lai, 2017; He et al., 2020). Thus, it is needed to understand the individual students' learning style, and the instructor's teaching style needs to be tuned to a certain extent. Further, Adnan and Anwar (2020) emphasized that online learning during the COVID-19 might be problematic specifically to tactile learners. Thus, compatible teaching and learning need to be ensured to increase the positive perception in the mind of undergraduates. Perceived security risk had the significant negative impact on the attitude (β= -0.034, p-value<0.05), supports H5. Similar results were reported in the previous studies too (Lee, 2009; Sanayei and Bahmani, 2012; Liao et al., 2010; Xie et al., 2017). When engaging in real-time online classes, students feel that they may be watched and tracked by some party, which will become the motivation hindering factor later (Kim, 2021). Thereby, Perceived Security Risk on the online platforms will be assumed to be higher. Appropriate security measures therefore need to be ensured in order to increase the positive feeling on the real-time online learning.

74.7% of the variance in the perceived behavioral control has been demonstrated by its identified antecedents namely perceived self-efficacy and facilitating conditions. The study revealed that perceived self-efficacy had the positive effect on the perceived behavioral control (β= 0.507, p-value<0.05), supporting H8 proven by (Cheon et al., 2012; Leejoeiwara, 2013; Tagoe and Abakah, 2014; Lai, 2017; Gomez-Ramirez et al., 2019). This finding shows that as learners' confidence in their ability increases, they may perceive real-time online learning positively. Besser et al. (2020) discovered a discrepancy between student's actual performance and their ideal performance in terms of their expectations and standards. It may be due to the less evaluation of their ability to perform well since they are isolated and distanced from the immediate access of the university. Therefore, it is the prime responsibility of each student to enhance their self-confidence and positive belief in their ability of themselves. Followingly, facilitating conditions has positively influenced perceived behavioral control (β= 0.400, p-value<0.05), supports H9. The similar results were found in past researches (Lai, 2017; Leejoeiwara, 2013). The students may perceive real-time online learning as it does not require additional effort if they have required technical resources and operative knowledge, and other resources in hand.

Overall, intention to use the real time has been explained with the R2 value of 50.3% by the attitude, perceived behavioral control and subjective norm. Hypotheses namely H1 (β= 0.188, p-value<0.05), H7 (β= 0.312, p-value<0.05) and H6 (β= 0.327, p-value<0.05) were supported. Thus, Attitude (Cheon et al., 2012; Leejoeiwara, 2013; Tagoe and Abakah, 2014; Ismail and Hosseini, 2014; Lai, 2017; Hadadgar et al., 2016; Mangir et al., 2017; Yang and Su, 2017; Khasawneh, 2017; Buabeng-Andoh, 2018; Gomez-Ramirez et al., 2019; Clutterbuck et al., 2015; Nadlifatin et al., 2020; Ilyas and Zaman, 2020; Gao, 2020; He et al., 2020; Alfadda and Mahdi, 2021; Purwanto and Tannady, 2020; Bhatt and Shiva, 2020; Long and Khoi, 2020), perceived behavioral control (Cheon et al., 2012; Leejoeiwara, 2013; Tagoe and Abakah, 2014; Lai, 2017; Masruf and Teng, 2016; Hadadgar et al., 2016; Mangir et al., 2017; Yang and Su, 2017; Gomez-Ramirez et al., 2019; Clutterbuck et al., 2015; Nadlifatin et al., 2020; Ilyas and Zaman, 2020; Wang et al., 2020; Gao, 2020; He et al., 2020; Ngafeeson and Gautam, 2021) and subjective norm (Cheon et al., 2012; Leejoeiwara, 2013; Tagoe and Abakah, 2014; Lai, 2017; Masruf and Teng, 2016; Mangir et al., 2017; Yang and Su, 2017; Buabeng-Andoh, 2018; Gomez-Ramirez et al., 2019; Clutterbuck et al., 2015; Nadlifatin et al., 2020; Ilyas and Zaman, 2020; Wang et al., 2020; Kim et al., 2021) have the positive effect on the intention to use.

CONCLUSION

The study found a significant impact of Perceived Usefulness on Attitude. Hence, the universities can educate the undergraduates on the benefits of using real-time online learning, and it will help the universities to create positive attitudes among undergraduates towards using real-time online learning. Such positive attitudes can result in adopting real-time online learning more. It may help the universities to overcome poor attendance issues experienced in real-time online learning.

Followingly, Perceived Ease of Use has a significant positive impact on attitude. Students can be educated about how real-time online learning is convenient and easy to use. Thus, university administration can utilize help-desk facilities, training manuals, and video demonstrations to convince the students of the extent to which real-time online learning is easy to use, easy to access, and easy to understand in comparison with traditional learning. These should help to develop positive attitudes towards using real-time online learning. In addition to that, software developers should incorporate new features to make it more user-friendly and convenient to use. Thus, it will result in a positive attitude towards real-time online learning. Additionally, computer hardware and software designers can consider incorporating new features to accommodate the needs of physically disabled students, particularly those who are deaf. As a result, such students will also perceive real-time online learning to be more user-friendly and convenient. It will result in a more favorable attitude toward real-time online learning among these students.

It is discovered that Compatibility has a significant effect on Attitude. It is the prime responsibility of university administration, especially the Internal Quality Assurance Body of each university, to ensure that real-time online learning fits well with students' learning styles. It can be assured by employing frequent feedback mechanisms to assess the extent to which real-time online learning matches with learning style and learning expectation. With the Insights of the feedback, students can be advised through a series of workshops on how learning style needs to be improved to match the idea of real-time online learning. When real-time online learning becomes more compatible with students' learning styles, the positive attitude towards real-time online learning will be improved. Also, insights of the feedback should be communicated with the academic staff to clarify students' learning expectations. Thus, teaching style can be tailored to the learner's expectations. It has the potential to instill a positive attitude toward real-time online learning as it becomes more compatible with the learner's preferred learning style.

The study demonstrated that Perceived Self-Efficacy has a significant impact on Perceived Behavioral Control. With the assistance of the Career Guidance Unit, the university can organize a series of workshops and motivational speeches from experts to help students build their self-confidence. As a result, students will feel confident working independently in a real-time online learning system. It is not only the sole responsibility of the university to inculcate self-confidence in students. Also, each student must strive to drive up self-confidence and positive belief in their ability to learn via real-time online learning. Therefore, students will feel that real-time online learning is entirely within their control and will use real-time online learning well for their learning activities.

Also, the study has found a significant impact of Facilitation Conditions on Perceived Behavioral Control. Thus, the Sri Lankan government and relevant authorities of the university system must ensure that students have adequate technological resources, operative knowledge, and other required resources for learning. Further, the proposals for establishing computer laboratories in the rural areas, availability of affordable computing devices and internet, and facilities for technical support must be initiated at the university and government level to help the less-privileged students. Consequently, students will feel that real-time online learning is under their control and adopt it for learning activities. Most importantly, the study found a significant effect of Subjective Norm on Behavioral Intention to Use. Hence, there is a need for support from important people, especially friends, family, and academicians, to enhance the adoption of real-time online learning. The university can educate such influential individuals by hosting workshops on their role in students' adoption of real-time online learning. Consequently, with such essential people's positive influence and support, the adoption of real-time online learning will improve.

Limitations

Firstly, this study primarily focuses on Sri Lankan context. As Sri Lanka is a developing nation and online system is not adequately installed and practiced, the framework will be applicable. To enhance the use of this study in developed country the framework needs to be modified in order to cope their needs and challenges. Secondly, future studies can be emerged by combing qualitative and quantitative aspects to have a comprehensive view of student's perspectives of online learning. Thirdly, teacher's perspective can be further added and investigated. Finally, cross sectional studies can be developed in future.

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